GRASSROOTS JOURNALS

Grassroots Journal of Natural Resources, Vol.7 No.2 (August 2024)
ISSN: 2581-6853 | CODEN: GJNRA9 | Published by The Grassroots Institute
Website: https://grassrootsjournals.org/gjnr | Main Indexing: Scopus and WoS

ISSN 2581-6853 | 7(2) Aug 2024

M – 00407 | Research Article

Agricultural Vulnerability to Climate Change: A quantitative assessment for Odisha

Sk Mosharaf Hossain*[1], Hrudananda Atibudhi[2]
[1]Department of Agricultural Economics, Institute of Agricultural Sciences,
Siksha O Anusandhan (Deemed to be University), Bhubaneswar, India.
Email: mosharaf.ximb@gmail.com | ORCID: https://orcid.org/0000-0002-1164-4229
[2]Department of Agricultural Economics, Institute of Agricultural Sciences,
Siksha O Anusandhan (Deemed to be University), Bhubaneswar, India.
Email: hnatibudhi@rediffmail.com | ORCID: https://orcid.org/0009-0001-3153-2320
**Corresponding author*

How to cite this paper: Hossain, S.M. and Atibudhi, H. (2024). Agricultural Vulnerability to Climate Change: A quantitative assessment for Odisha. *Grassroots Journal of Natural Resources*, 7(2): 236-250. Doi: https://doi.org/10.33002/nr2581.6853.070212

Received: 21 June 2024
Reviewed: 26 July 2024
Provisionally Accepted: 26 July 2024
Revised: 30 July 2024
Finally Accepted: 31 July 2024
Published: 03 August 2024
Copyright © 2024 by author(s)

Publisher's Note: We stay neutral with regard to jurisdictional claims in published maps, permissions taken by authors and institutional affiliations.

This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/

Open Access

Executive (Chief) Editor
Dr. Hasrat Arjjumend
Associate Editors
Dr. Usongo Patience
Ms. Areej Sabir
This article is edited by Dr. Hasrat Arjjumend

Abstract

Odisha is considered one of the most vulnerable states in India, as recurrent climatic events strike it almost every year. The quantum of agricultural damage from floods and drought is colossal. The farming community, dominated by small and marginal landholders, are more vulnerable because of their weak coping capacity. The climate extremes are progressive and increasingly frequent. For agriculture to progress and sustain itself in such a scenario, the vulnerability of agriculture in the state needs to be comprehensively assessed. The study was primarily a district-level analysis, employing the IPCC framework and evaluating the degree of vulnerability by measuring three dimensions: exposure, sensitivity, and adaptive capacity. Using secondary data from 17 indicators, the study constructed indices for three dimensions separately and finally arrived at the overall vulnerability index. Based on their exposure, sensitivity, and adaptive capacity index scores, Jharsuguda, Bolangir, and Bhadrak were identified as the three most vulnerable districts. Conversely, Koraput, Kandhamal, and Malkangiri were found to be the three least vulnerable districts. Regarding exposure to different vulnerability-causing factors, Bolangir, Jharsuguda, and Subarnapur were at the top. Khorda, Balasore, and Bhadrak recorded high sensitivity scores. Despite the high scores of exposure and sensitivity, some districts showed high adaptive capacity to reduce the overall vulnerability score. It suggests that boosting adaptive capacity is a major driver in reducing agriculture vulnerability. The general pattern was that northern districts are more exposed to climate shocks, whereas coastal districts are highly sensitive. The districts from the central region, such as Angul, Koraput, Kandhamal, and Kalahandi, are less vulnerable. The drivers for these index scores will help formulate district-specific measures to make farmers and overall agriculture less vulnerable.

Keywords

Agriculture vulnerability; Exposure; Sensitivity; Adaptive capacity; IPCC

Introduction

Historically, Odisha is a climate-vulnerable state in India. The colossal impact of the extremes in climate on agriculture production and farmers' livelihood remains a policy concern. Besides cyclones and floods, drought strikes the state almost every year. While the coastal districts are prone to floods, the western parts face water scarcity during crop seasons. The uneven rainfall distribution during monsoon months and inadequate irrigation facilities compound the problems for farmers. The delay in the monsoon onset prevents crop sowing, where erratic rainfall causes damage to crop growth during different phases. The late onset of monsoon and heavier-than-normal rainfall during September and October often harm rice crops in coastal districts (Das, 2012). In Odisha, only 38% of the area has irrigation coverage, and 62% of the cultivated area relies on monsoon rain (Atibudhi, 2015). During the last 50 years, from 1970 to 2019, the state was hit by declared drought 21 times and suffered a rainfall deficit in 33 years. In recent times, 2015 witnessed severe drought when 27 of 30 districts were declared drought-hit (GoO, 2022). The increasing frequency of such climatic events adversely impacts the progress in the agriculture sector. The normal monsoon starts in the second week of June. The rainfall is highly skewed from June to September, when 80% of the annual rainfall occurs (GoI, 2018). The IPCC4 (2022) report estimated a temperature rise of 2.7-4.3°C in temperature by the 2080s, causing an 88 cm sea level increase by 2100, and states like Odisha have to embrace many worst-case scenarios. About 91% of the farmers in India are small or marginal holders (NSSO, 2021). The effect of such drought-induced calamities will be strongly felt in the agrarian economy, where farming communities are dominated by smallholders. In 2017, over 50 per cent of crop damage was estimated to be 0.171 million hectares. In 2015-16, 29176 villages in 28 Districts were hit by drought, leading to one-third of crop area damage. The yield loss (4-5%) can be foreseen by 2025 in the rice-wheat cropping system in India (GoO, 2013). This potential loss in agricultural yield should be a cause for concern. The fluctuation of yield and production resulting from such climate vulnerability will have enormous implications for developing states like Odisha's food and nutrition security.

The first approach to address such vulnerability is the precise spatial assessment of the situation. The assessment will aid in implementing potential adaptive and mitigation measures to offset the negative impact. Globally, quantitative assessment is the standard practice used to evaluate the occurrence and extent of climate vulnerability and identify potential measures. Vulnerability in development discourse is a complex phenomenon. According to IPCC1 (2001), exposure, sensitivity, and adaptive capacity are three interconnected components that define the vulnerability level. IPCC Third Assessment Report (IPCC2, 2013) stated that vulnerability is "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes". Conceptually, exposure indicates a "system's frequency, occurrence, and proximity to the hazards"; sensitivity defines the degree to which climate variability or change affects a system or species adversely or beneficially (IPCC3, 2014). The "ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" is the adaptive capacity (IPCC3, 2014). While exposure and sensitivity are positively related to vulnerability, the functional relationship of adaptive capacity is negative. An index-based measurement of vulnerability following this framework will

broaden the knowledge and understanding of the subject matter. Against this backdrop, the study attempted to assess relative vulnerability across 30 districts of Odisha. The district-wise assessment and comparative analysis will help tackle the agriculture vulnerability more specifically.

This study constructed indices for exposure, sensitivity, and adaptive capacity and, by combining these, finally developed a vulnerability index for all 30 districts. This index is a crucial tool for policymakers, researchers, and stakeholders as it provides a comprehensive understanding of each district's climate vulnerability, enabling targeted and effective mitigation and adaptation measures.

The study objectives:

I. It aimed at measuring the source and quantum of different components of agricultural vulnerability across 30 districts in Odisha;
II. To map the vulnerability for studied districts and formulate mitigation measures.

Material and Methods

The vulnerability analysis in this study has three dimensions—exposure, sensitivity and adaptive capacity. The study reviewed secondary literature and selected relevant indicators for the construction of exposure, sensitivity and adaptive capacity indices. After that, district-level secondary data was collected from multiple sources for each indicator under three dimensions. The major data sources were 1) Odisha Agriculture Statistics (2018-19), Directorate of Agriculture and Food Production, Government of Odisha, 2) Report on Agriculture Census, Odisha, 2015-16, Directorate of Economics and Statistics, Odisha, Bhubaneswar, 3) Odisha Economic Survey 2022-23, Planning and Convergence Department Directorate of Economics and Statistics Government of Odisha, 4) Agricultural Statistics at a Glance 2018, Directorate of Economics and Statistics, Ministry of Agriculture and Farmers' Welfare, Government of India, and 5) Five decades of Odisha Agriculture Statistics (2020), Directorate of Agriculture and Food Production, Government of Odisha. The latest available data was obtained for all 30 districts in the state. The number of selected indicators for Exposure, Sensitivity and Adaptive Capacity (AC) were two, nine and six, respectively. Thus, a total of 17 indicators were evaluated to analyze vulnerability.

Table 1: The list of indicators under three vulnerability dimensions is presented below

Component	*Indicator*	*Measurement unit*	*Data Source and year*	*Functional relationship with vulnerability*
Exposure	Variance in rainfall (Per cent, Coefficient variation)	Percent	Calculated using district-wise rainfall data from 1994-2023 (source: https://srcodisha.nic.in/rain_fall.php)	Positive
Exposure	Rainfall (mm) SRC, 2022	Millimeter	Sourced and compiled data from Odisha Rainfall Monitoring System Portal	Negative

Component	*Indicator*	*Measurement unit*	*Data Source and year*	*Functional relationship with vulnerability*
			(https://srcodisha.nic.in/rain_fall.php)	
Sensitivity	Irrigated area	Percent	Agricultural Statistics, GoO 2018-19	Negative
Sensitivity	Forest Area (Per cent of total geographical area), Agricultural Statistics 2018-19	Percent	Agricultural Statistics, GoO 2018-19	Negative
Sensitivity	Average landholding size (ha)	Hectare	Agriculture Census, GoO 2015-16	Negative
Sensitivity	Cropping intensity (Per cent)-Agricultural statistics 2018-19	Percent	Agricultural Statistics, GoO 2018-19	Negative
Sensitivity	Small and marginal farmers (Per cent of total farmers)	Percent	Agricultural Statistics, GoO 2018-19	Positive
Sensitivity	Stage of Ground Water Development	Percent	Central Ground Water Board, 2014	Negative
Sensitivity	Population growth	Percent	Census of India, 2011	Positive
Sensitivity	Population Density	Number	Census of India, 2011	Positive
Sensitivity	Percentage of rural population	Percent	Census of India, 2011	Negative
Adaptive Capacity	Literacy rate	Percent	Census of India, 2011	Positive
Adaptive Capacity	Crop diversification index	Percent	Calculated by Authors, 2023	Positive
Adaptive Capacity	Net Sown Area	Hectare	Agricultural Statistics, GoO 2018-19	Positive
Adaptive Capacity	Multidimensional Poverty index	Percent	National Multidimensional Poverty Index (MPI), 2023, A Progress Review, NITI Aayog, 2023	Positive
Adaptive Capacity	Per Capita GDP 2018-10 (SRC, at a constant price of 2011-12)	Rupees	Odisha Economy, District Income 2018-19	Negative
Adaptive Capacity	Productivity of food grains (kg/ha). Agricultural Statistics-2018-19	kg/ha	Agricultural Statistics, GoO 2018-19	Negative

Data normalization

The data for each indicator comes in different units. Therefore, all indicator values were normalized to create a common and comparable scale. Indicator normalisation uses maximum and minimum values based on the indicators' functional relationship with vulnerability (Žurovec, Čadro and Sitaula, 2017). The collected data was first arranged in an N X M matrix, where N denotes districts and M is the value for each indicator in three dimensions.

When an indicator has a positive functional relation with vulnerability, its value is normalized using the following formula. The matrix will have N rows and M columns. Thus, X_{ij} is the index value of the i^{th} indicator in the j^{th} district.
$Y_{ij} = x_{ij} - Min\{x_{ij}\} / Max\{x_{ij}\} - Min\{x_{ij}\}$ (UNDP, 1990)
Data normalisation uses fowling expression for indicators negatively related to the vulnerability.
$Y_{ij} = Max\{x_{ij}\} - x_{ij} / Max\{x_{ij}\} - Min\{x_{ij}\}$
Where Y_{ij} is the index for the i^{th} indicator in the j^{th} district
Min{xij} and Max{xij} are the minimum and maximum values of the i^{th} indicator among all (N) districts.
For this study in Odisha, N= 1, 2, ……., j,….30 as there are 30 districts in the state.
The number of indicators i =1,2,3,……., M. 17 indicators were analysed.

Weightage assignment

After all indicators were normalized, weightage was assigned using Principal Component Analysis (PCA). PCA assumes a linear relationship among variables. This method overcomes the inherent problems of biases, which are often detected in other methods (Sendhil *et al*., 2018). This PCA technique also considers the variance of the indicator variables and assigns lower weightage to the variables with high variance and vice versa. The statistical software STATA was used to perform this analysis. In the analysis, the squared values of factor loading of each indicator from the first Principal Component (PC) were used as a weight for the individual indicator. The first PC has the highest eneigenvalue.

Categorization of districts based on index value

The study ranked all 30 districts based on their scores in all indices. Exposure, sensitivity, and adaptive capacity are grouped into four groups -- least, moderate, high, and very high.

Category 1 (Very High): When a district's index score is estimated to be 0.76 or more, it is considered very high for that particular component (exposure, sensitivity, and adaptive capacity).

Category 2 (High): The districting scoring between 0.51 and 0.75 in these three indicators are grouped as high for exposure, sensitivity, and adaptive capacity.

Category 3 (Medium): Districts with index values between 0.26 and 0.50 were categorized as moderate in terms of exposure, sensitivity, and adaptive capacity.

Category 4: (Low): Districts under this category are least as measured for exposure, sensitivity, and adaptive capacity, and the index value for each of these three indicators is less than 0.25.

The study also estimated district-wise vulnerability by combining exposure, sensitivity and adaptive capacity indices (Simple addition). Vulnerability Index (VI) = Exposure Index (EI) + Sensitivity Index (SI) — Adaptive Capacity (AC). Based on the VI score, the districts were ordered and described.

Results and Discussion

Exposure across Districts

Exposure refers to the degree to which a system's proximity to a hazard is estimated by analysing two indicators. The assessment revealed that the western part of the state is more vulnerable than the coastal plain. While Bolangir, a district in western Odisha, scores the highest exposure index (0.871), Balasore, from the coastal belt, recorded the lowest level of exposure (0.090). Bolangir, Subarnapur, and Jharsguda are highly exposed districts with index values of 0.871, 0.791, and 0.783, respectively (Figure 1). Nuapada, Bargarh, Puri, Boudh, Ganjam, Kalahandi, Debgarh, Sambalpur, and Anugul have high exposure index values ranging from 0.516 to 0.607. Low rainfall and higher variation in rainfall distribution are recurrent features in western districts of the state. Farmers often face water shortages during the sowing and crop growth period.

There are 11 districts with exposure index values ranging from 0.269 to 0.495, mostly in the coastal region. Seven districts — Dhenkanal, Koraput, Mayurbhanj, Nabarangpur, Jajpur, Cuttack, and Balaosre — had a low level of exposure to vulnerability and the index ranged from 0.090 to -0.257. Thus, regarding exposure to vulnerability, districts like Bolangir, Sonepur, and Jharsuguda require comprehensive remedies to mitigate the negative effects on agriculture practices and outcomes. Mayurbhanj is the largest district in the state and is dominated by the SC and ST population with 66% (Census of India, 2011), but has a low exposure index, suggesting the possibility of vulnerability reduction with increased adaptive capacity.

The irrigation coverage in these districts is limited (20-30%). The high dependency on scanty and erratic rainfall is often a cause for farmers' vulnerability. The coefficient of variation for the studied districts varied from 16% in Dhenkanal to 24% in Subarnapur. The three highly exposed districts — Bolangir Sonepur and Jgarusuguda — had 23-24% rainfall variations. The high coefficient of variation is the prime reason for aggravating exposure levels in districts of the western part of the state.

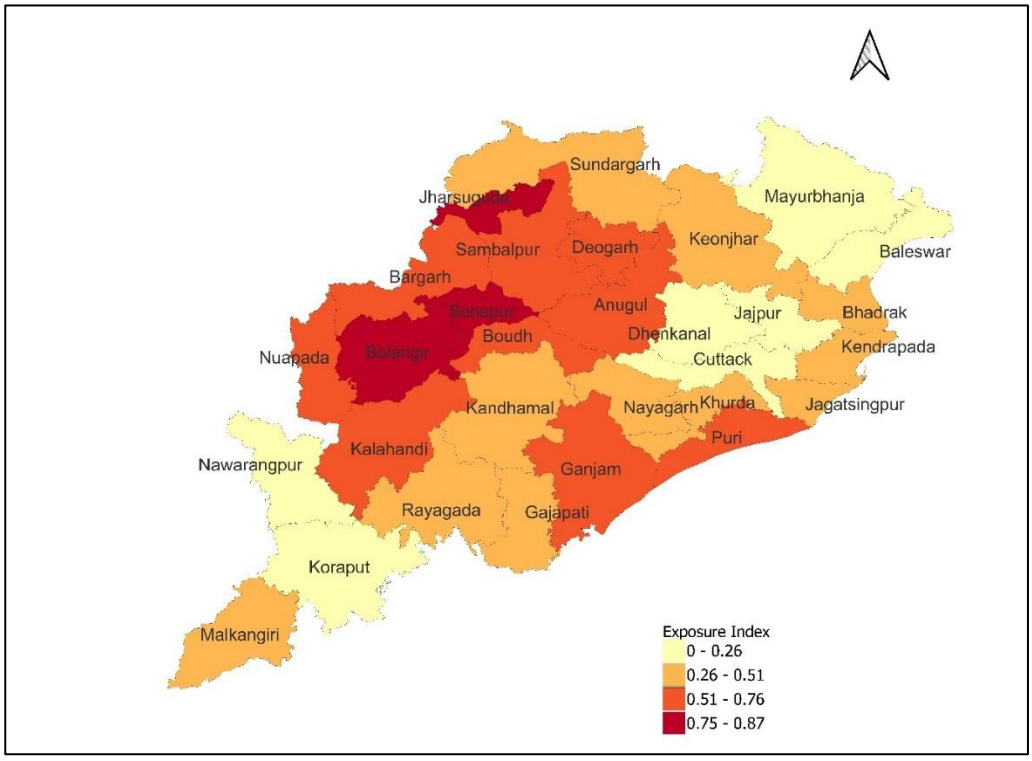

Figure 1: Exposure Index across districts

Sensitivity across Districts

The study used eight indicators to measure farmers' sensitivity to climate events. It comprehensively assessed the irrigation situation, size of operational holding, cropping intensity, the share of small and marginal farmers, groundwater recharge, population density, and growth to determine the district-level sensitivity. The high index value explains that the district is susceptible to climate factors and, thus, more vulnerable.

Sambalpur district, one of the highly exposed districts, was found to be the least sensitive. On the other hand, Balasore, the least exposed district, measured the highest sensitive score. This indicates that the incidence of exposure is not always positively correlated with the sensitivity level. A moderate level of sensitivity (0.49) was measured at the state level, and as many as 16 districts recorded higher than state sensitivity scores. Another eleven districts showed index scores between 0.26 and 0.50. Koraput, Kalhandi, Bargarh, Boudh, Nabarangpur, Gajapati, Rayagada, Nuapada, Sundargarh, Subarnapur, Kandhamal and Deogarh, mostly from the western and southern regions of the state are in this category. The highly sensitive category included 13 districts, and their scores vary from 0.513 in Subarnapur to 0.74 in Jagatsinghpur. Balasore, Bhadrak, and Khorda are three highly sensitive districts whose index values exceeded 0.75. It is important to note that highly sensitive districts are mostly from coastal areas, unlike exposure. Interestingly, the sensitivity decreases as one moves from east to west.

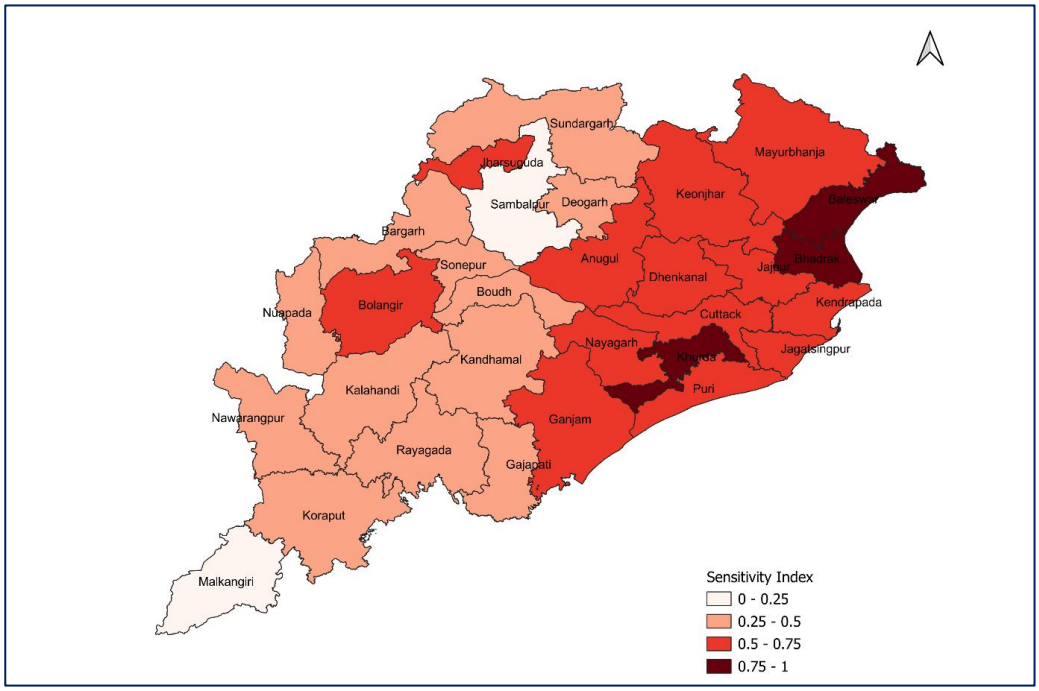

Figure 2: Sensitivity index across districts

Low landholding size, high proportion of small and marginal farmers, poor groundwater development, and high population density contribute more to the sensitivity index. Thus, these are the major drivers for the districts' higher sensitivity. The less irrigated area and low cropping intensity are other potential reasons for high climate sensitivity in studied districts.

In districts of Jajpur, Bhadrak, Jagatsinghpur, Cuttack, and Khorda, high population density majorly contributes to the sensitivity. However, in the western and southern districts, like Sambalpur, Bargarh, Koraput, Kalahandi, Boudh, Nabrangpur, Debgarh, Nuapada, Kandhamal, and Malkangiri, sensitivity is driven by a high proportion of small and marginal farmers, low cropping intensity, less landholding size, and low groundwater development. High population density is also a leading reason for sensitivity in Khorda and Jajpur. The declining forest area compounds the sensitivity in districts like Bargarh, Kalahandi, Bolangir, Koraput, Subarnapur, Puri, and Jharsuguda. Contrastingly, Malkangiri, despite being the poorest district (Niti Aayog, 2023), has a very low level of sensitivity.

Adaptive Capacity

The adaptive capacity (AC) explains the strengths of an agriculture system that minimises the impact of exposure and sensitivity. The higher the adaptive capacity, the less vulnerable the system. A region with high adaptive capacity offsets the effect of high exposure and sensitivity. Six indicators, including cropping intensity, net sown area, multidimensional poverty index, literacy rate, per capita GDP, and productivity of food grains, were measured to develop the index for adaptive capacity. The overall AC for the state was high (0.56). Anugul is the only district with a high adaptive capacity

(0.76). There are 10 districts in the 'High' category, and the calculated ACI ranges from 0.5096 (Boudh) to 0.6572 (Kandhamal). Raygada, Keonjhar (Kendujhar), Koraput, Dhenkanal, Cuttack, Sundargarh, Subarnapur, and Gajapati also have high adaptive capacity. High levels of crop diversification, good productivity of food grain crops and per capita GDP have been instrumental in stronger adaptive capacity in these districts. Koraput to Keonjhar has high adaptive capacity and is driven by a diversified cropping system. Bhadrak, Khorda, Balasore, Kendrapara, Jagtsighpur, and Ganjam have less adaptive capacity. The low adaptive capacity commensurate with the low income of the districts and it corroborates with the study conducted by Žurovec, Čadro and Sitaula (2017).

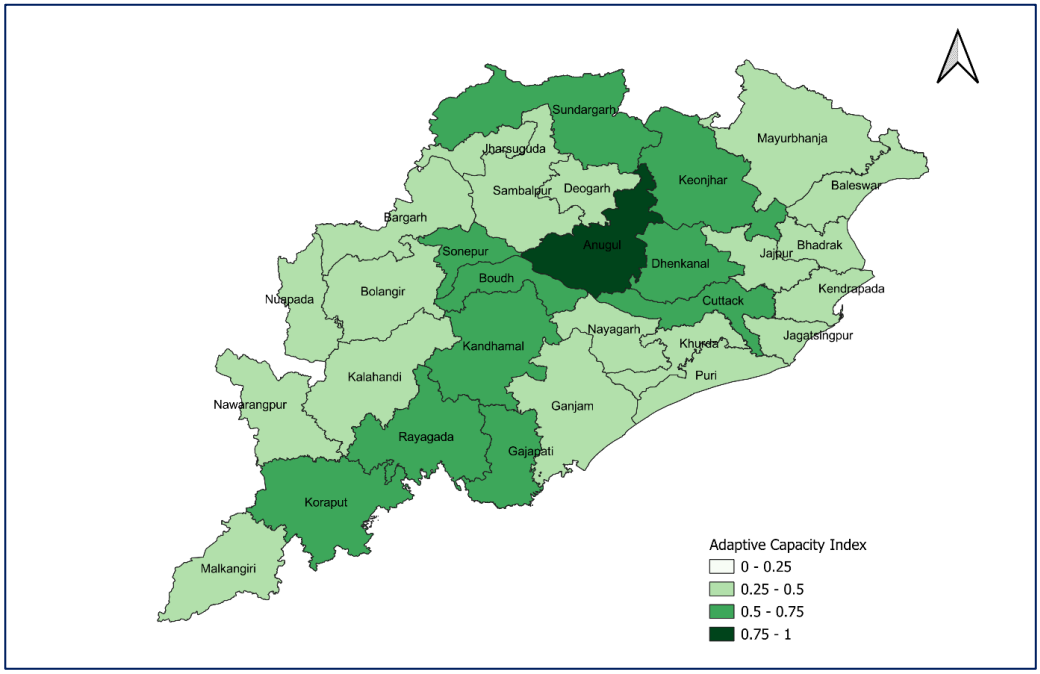

Figure 3: Adaptive Capacity Index for districts

The Comprehensive Vulnerability

Exposure Index (EI) and Sensitivity Index (SI) minus the Adaptive Capacity Index (ACI) were combined to estimate the overall vulnerability for districts as well as the state. The average vulnerability index value for Odisha was 0.386 (medium). Wide variation in vulnerability was noted across districts because of different exposure and sensitivity scores. The vulnerability index value ranged from 0.094 to 0.999. Five districts were found to be as highly vulnerable, and another eight were in the "high" category. Jharsuguda was the most vulnerable district, and its VI score was 0.999, followed by Bolangir (0.974), Bhadrak (0.820), Kendrapara (0.784), and Puri (0.772). High EI, SI, and low ACI largely cause vulnerability in Jharsuguda, Bolangir, and Puri. However, in Bhadrak, less EI, high SI, and low ACI create high vulnerability. The same applies to the Khordha, Jajpur, Balasore, and Mayurbhanj districts. Koraput was found to be the least vulnerable district, with a score close to 0. Kandamal, Malkangiri, Dhenkanal, and Nabarangpur districts also showed low vulnerability. The low EI, SI and higher ACI minimised the vulnerability score in the Anugul, Cuttack, Rayagada, and Kendujhar

districts. Interestingly, the most vulnerable districts are in the state's western or coastal parts. The state's northern, southern, and central districts are less vulnerable.

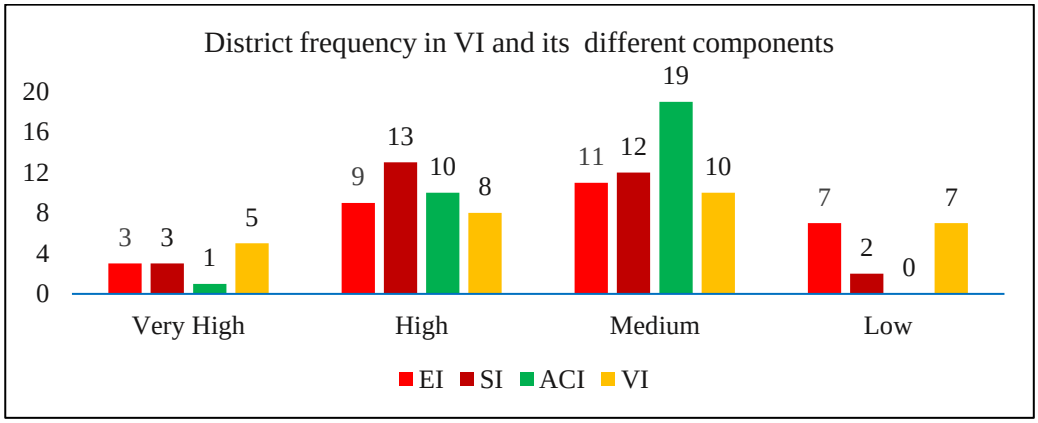

Figure 4: Frequency of districts in vulnerability and its components

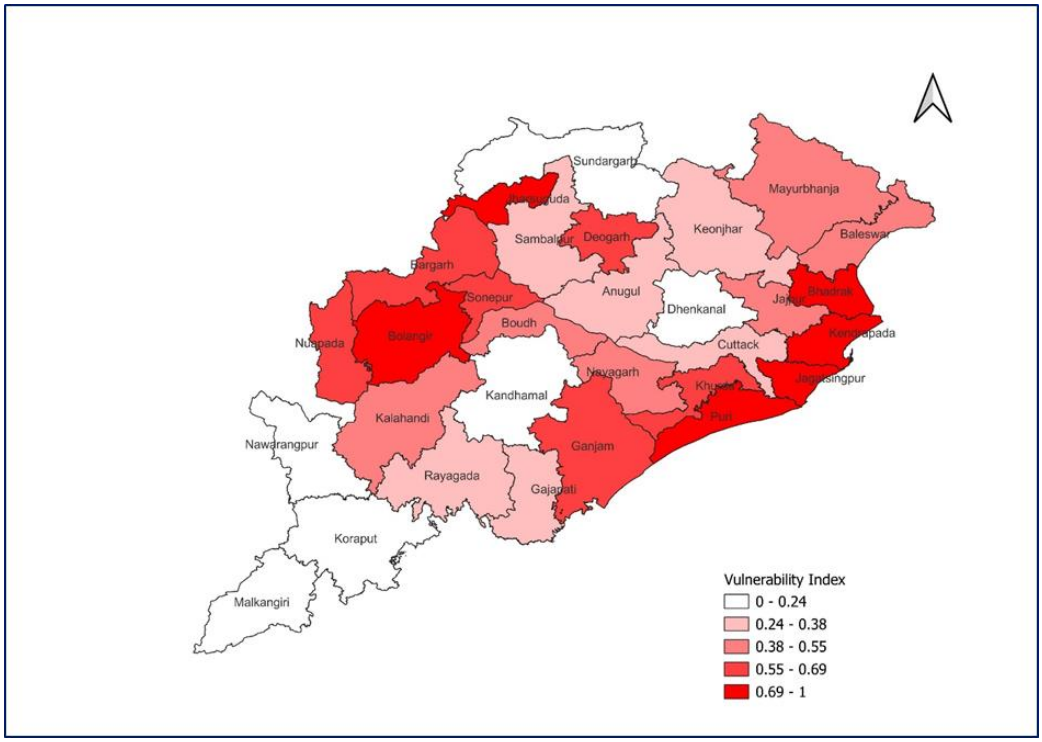

Figure 5: State's vulnerability map based on the index scores

The correlation between Exposure, Sensitivity, Adaptive Capacity and Vulnerability

Since vulnerability is a composite index derived from exposure, sensitivity, and adaptive capacity, the study analyzed their correlational direction and strength with vulnerability. The index values of these three parameters for 30 districts were evaluated against the corresponding vulnerability score. As expected, a high negative correlation was found between vulnerability and adaptive capacity (-0.66). The high positive correlation

coefficient (0.60) between exposure and vulnerability also explains their strong association. Interestingly, sensitivity does not strongly relate to the vulnerability scores; the correlation coefficient is 0.40. This is most likely because of the high adaptive capacity that minimizes the overall vulnerability score despite the high sensitivity.

Table 2: District-wise EI, SI, ACI and overall vulnerability index value.

#	*District*	*Exposure Index (EI)*	*Sensitivity Index (SI)*	*Adaptive Capacity Index (ACI)*	*Vulnerability Index (EI+SI-ACI)*	*Rank*
1	Anugul	0.516	0.539	0.767	0.287	23
2	Balangir	0.871	0.513	0.409	0.974	2
3	Balasore	0.090	0.788	0.454	0.424	17
4	Bargarh	0.607	0.349	0.322	0.634	11
5	Bhadrak	0.313	0.768	0.261	0.820	3
6	Boudh	0.594	0.368	0.510	0.453	14
7	Cuttack	0.172	0.676	0.543	0.305	21
8	Debagarh	0.596	0.418	0.440	0.574	12
9	Dhenkanal	0.257	0.541	0.612	0.186	27
10	Gajapati	0.416	0.396	0.511	0.301	22
11	Ganjam	0.591	0.535	0.457	0.669	9
12	Jagatsinghpur	0.429	0.739	0.459	0.710	6
13	Jajpur	0.181	0.693	0.433	0.442	15
14	Jharsuguda	0.783	0.539	0.322	0.999	1
15	Kalahandi	0.564	0.346	0.476	0.435	16
16	Kandhamal	0.269	0.417	0.657	0.029	29
17	Kendrapara	0.350	0.717	0.284	0.784	4
18	Kendujhar	0.439	0.523	0.650	0.312	20
19	Khordha	0.349	0.765	0.466	0.648	10
20	Koraput	0.242	0.277	0.613	-0.094	30
21	Malkanagiri	0.336	0.225	0.431	0.130	28
22	Mayurbhanj	0.233	0.548	0.379	0.402	18
23	Nawarangpur	0.230	0.381	0.397	0.214	26
24	Nayagarh	0.423	0.527	0.414	0.535	13
25	Nuapada	0.721	0.402	0.437	0.686	8
26	Odisha	0.451	0.493	0.558	0.386	NA
27	Puri	0.598	0.547	0.374	0.772	5
28	Rayagada	0.495	0.397	0.651	0.241	24
29	Sambalpur	0.537	0.221	0.402	0.356	19
30	Subarnapur	0.791	0.413	0.517	0.687	7
31	Sundargarh	0.345	0.410	0.523	0.232	25

Conclusion

This experimental study asserted the hypothesis of high vulnerability across districts with high sensitivity to different climatic factors. However, contrary to the hypothesis, high adaptive capacity in several districts was reported. The research exercise comprehensively assessed the vulnerability level, considering the exposure, sensitivity, and adaptive capacity score. The analysis was at the district and state levels so a comparison could be made. Overall, the vulnerability level is severe as 13 districts fall in the category of 'very high' and 'high'. Importantly, the high level of adaptive capacity was reported by most districts, and it has counterbalanced the impact of exposure and sensitivity. Thus, it has highlighted that adopting measures to enhance the adaptive capacity is a robust mechanism and should be a policy priority to manage the damages emanating from factors responsible for high exposure and sensitivity. Interestingly, a high degree of exposure was reported from northern districts like Bolangir, Sonepur, Jharsuguda, Nuapada, Nabrangpur, etc. However, coastal districts, such as Balasore, Bhadrak, Khurda, Mayurbhanj, Puri, etc., were found to be highly sensitive. The districts in the middle of the state, like Anugul, Boudh, Kandhamal, Rayagada and Koraput, showed high adaptive capacity; thus, these areas are more resilient to climatic events. The overall vulnerability score for these districts is also low. The study recommends a district-wide understanding of different factors under three vulnerability components to devise a sustainable pathway to mitigate the climate impact, especially for the farming community. There are several measures already underway to build coping capacities and minimize sensitivity. This includes farmers' welfare schemes like direct cash transfers, incentives for crop diversification, minimum support prices, etc. The farmers in vulnerable regions need to be well-linked to these schemes to lessen the vulnerability burden.

References

Atibudhi, H. (2015). Pattern of Agricultural Diversification in Odisha. In: Ghosh, M., Sarkar, D., Roy, B. (eds.), *Diversification of Agriculture in Eastern India. India Studies in Business and Economics*. Springer, New Delhi. DOI: https://doi.org/10.1007/978-81-322-1997-2_6.

Das, S.R. (2012). Rice in Odisha. *IRRI Technical Bulletin*, 16. Los Baños (Philippines): International Rice Research Institute, 31 p.

GoI (2013a). Dynamic Ground Water Resources of India (2013), Central Ground Water Board Ministry of Water Resources, River Development& Ganga Rejuvenation, Government of India. Available online at: https://nwm.gov.in/sites/default/files/Dynamic-GWRE-2013.pdf (accessed 23 June 2024).

GoI (2018). Agricultural Statistics at a Glance. Directorate of Economics and Statistics, Ministry of Agriculture and Farmers' Welfare, Government of India (GoI), New Delhi.

GoO (2013b). Disaster Management Plan for Odisha Department of Health and Family Welfare, Government of Odisha. Available online at: https://health.odisha.gov.in/sites/default/files/2020-02/Disaster_Management.pdf (accessed 23 June 2024)

GoO (2022). Annual Report on Natural Calamities 2021-22, Revenue and Disaster Management Department, Special Relief Commissioner, Government of Odisha,

Bhubaneswar. Available online at: https://srcodisha.nic.in/annualReport/4vP2yUSqANNUAL%20REPORT%20ON%20NATURAL%20CALAMITIES,2021-22.pdf (accessed 23 June 2024).

IPCC (2022). *Climate Change 2022: Impacts, Adaptation, and Vulnerability*. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge, UK and New York, NY, USA: Cambridge University Press, 3056 pp. DOI: https://doi.org/10.1017/9781009325844.

IPCC1 (2001). *Climate Change 2001: The Scientific Basis.* Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change [Houghton, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.)]. Cambridge, United Kingdom and New York: Cambridge University Press.

IPCC2 (2013). *Climate Change 2013: The Physical Science Basis.* Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, pp.1535. DOI: https://doi.org/10.1017/CBO9781107415324.

IPCC3 (2014). *Climate Change 2014: Synthesis Report.* Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, pp.151.

Niti Ayog (2023). National Multi-Dimensional Poverty Index, A progress review 2023. Government of India, New Delhi. Available online at: https://www.niti.gov.in/sites/default/files/2023-08/India-National-Multidimentional-Poverty-Index-2023.pdf (accessed 23 June 2024).

Sendhil, R., Jha, A., Kumar, A. and Singh, S. (2018). Extent of Vulnerability in Wheat Producing Agro-Ecologies of India: Tracking from Indicators of Cross-Section and Multi-Dimension Data. *Ecological Indicators*, 89: 771-780. DOI: https://doi.org/10.1016/j.ecolind.2018.02.053.

UNDP (United Nations Development Programme) (1990). Human Development Report: Concept and Measurement of Human Development; United Nations Development Programme, New York, NY, USA.

Žurovec, O., Čadro, S. and Sitaula, B.K. (2017). Quantitative Assessment of Vulnerability to Climate Change in Rural Municipalities of Bosnia and Herzegovina. *Sustainability*, 9(7): 1208. DOI: https://doi.org/10.3390/su9071208.

Authors' Declarations and Essential Ethical Compliances

Authors' Contributions (in accordance with ICMJE criteria for authorship)

Contribution	*Author 1*	*Author 2*
Conceived and designed the research or analysis	Yes	Yes
Collected the data	Yes	No
Contributed to data analysis & interpretation	Yes	Yes
Wrote the article/paper	Yes	No
Critical revision of the article/paper	Yes	Yes
Editing of the article/paper	Yes	Yes
Supervision	No	Yes
Project Administration	No	Yes
Funding Acquisition	No	No
Overall Contribution Proportion (%)	70	30

Funding
No financial support was received for the research and writing of this article.

Research involving human bodies or organs or tissues (Helsinki Declaration)
The author(s) solemnly declare(s) that this research has not involved any human subject (body or organs) for experimentation. It was not a clinical research. The contexts of human population/participation were only indirectly covered through literature review. Therefore, an Ethical Clearance (from a Committee or Authority) or ethical obligation of Helsinki Declaration does not apply in cases of this study or written work.

Research involving animals (ARRIVE Checklist)
The author(s) solemnly declare(s) that this research has not involved any animal subject (body or organs) for experimentation. The research was not based on laboratory experiment involving any kind animal. The contexts of animals were only indirectly covered through literature review. Therefore, an Ethical Clearance (from a Committee or Authority) or ethical obligation of ARRIVE does not apply in cases of this study or written work.

Research on Indigenous Peoples and/or Traditional Knowledge
The author(s) solemnly declare(s) that this research has not involved Indigenous Peoples as participants or respondents. The contexts of Indigenous Peoples or Indigenous Knowledge were only indirectly covered through literature review. Therefore, prior informed consent (PIC) of the respondents or a Self-Declaration in this regard is not applicable for this article.

Research involving Plants
The author(s) solemnly declare(s) that this research has not involved the plants for experiment and field studies. Some contexts of plants are also indirectly covered through literature review. Yet, during this research the author(s) obeyed the principles of the Convention on Biological Diversity and the Convention on the Trade in Endangered Species of Wild Fauna and Flora.

Research Involving Local Community Participants (Non-Indigenous) or Children
The author(s) solemnly declare(s) that this research has not directly involved any local community participants or respondents belonging to non-Indigenous peoples. Neither this study involved any child in any form directly. The contexts of different humans, people, populations, men/women/children and ethnic people were only indirectly covered through literature review. Therefore, an Ethical Clearance (from a Committee or Authority) or prior informed consent (PIC) of the respondents or Self-Declaration in this regard does not apply in cases of this study or written work.

(Optional) PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)
The author(s) has/have NOT complied with PRISMA standards. It is not relevant in case of this study or written work.

Competing Interests/Conflict of Interest
Author(s) has/have no competing financial, professional, or personal interests from other parties or in publishing this manuscript. There is no conflict of interest with the publisher or the editorial team or the reviewers.

Attribution and Representation
All opinions and mistakes are the author(s)' own and cannot be attributed to the institutions they represent. The publisher is also not responsible either for such opinions and mistakes in the text or graphs or images.

Rights and Permissions

Open Access. This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third-party material in this article are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit http://creativecommons.org/licenses/by/4.0/.

***

To see original copy of these declarations signed by Corresponding/First Author (on behalf of other co-authors too), please download associated zip folder [Declarations] from the published Abstract page accessible through and linked with the DOI: https://doi.org/10.33002/nr2581.6853.070212.